Chapter 11

Is it possible to feel good and bad at the same time? New evidence on the bipolarity of mood-state dimensions

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11.1 Introduction

Is it possible to feel good and bad at the same time? A simple question, it seems, and one which should have a simple answer. However, this question is neither simple nor clear as the intensive and ongoing discussions at least since Wundt (1896) reveal (see, e.g., Beebe-Center, 1932; Diener, 1999; Diener & Emmons, 1985, Eid, Notz, Schwenkmezger & Steyer, 1994; Egloff, 1998; Green, Goldman & Salovey, 1993; Russell & Carroll, 1999; Tellegen, Watson & Clark, 1999; Schimmack, 2001; Vautier & Raufaste, 2002; Watson, 1988). One reason why this question is not so simple is because it lacks clarity in specifying what it refers to. Is it feelings or is it mood states we are considering? We distinguish *feelings* from *mood states* by the fact that feelings are directed towards or are centered upon an object. For example, I can feel happy, because someone said that he or she liked my work, and I can feel sad, because my dear aunt died recently. In this context, "happy" and "sad" refer to feelings. Hence, I can feel happy with respect to one object and sad with respect to another one, more or less at the same time, although in such a case the intensity of both feelings cannot be strong (cf., e.g., Bradburn, 1969).

In contrast to feelings, *mood states* are not focused upon an object. We simply feel happy or sad without any obvious or conscious reason. Using the figure-ground metaphor, feelings may be compared to figures, whereas mood states are the background against which figures are perceived. Note that in this context the same words "happy" and "sad" refer to psychologically different phenomena: mood states instead of feelings. *Considering these mood states*, we believe that it is not possible to feel good and bad at the same time. In more theoretical terms this means that we can construct a single ("bipolar") dimension with two opposite poles, extremely bad at one side and extremely good at the other.

Even when it has been clarified which empirical and psychological phenomena are to be considered, there is still a major obstacle hindering clear and unanimous empirical findings, namely using inappropriate designs and inappropriate models for data analysis. First of all, we believe that a cross-sectional design is not appropriate for answering our question of bipolarity. One reason for this is that self-reports of mood states are not easily comparable between different individuals. The same rating on the same item may mean different things for different persons. This problem is due to response styles with respect to which persons differ. Although some attempts have been made to control for acquiescence (see, e.g., Green et al., 1993; Tellegen et al., 1999), other response styles may still mask the true dimensional structure in cross-sectional studies. We believe that response styles can be more easily and more completely controlled for in longitudinal studies, because these response styles are part of the individual differences which are stable over time (see, e.g., Schimmack, 2001, p. 83). In this paper, we will show how controlling for such response styles can be achieved.

The second obstacle mentioned above is that often inappropriate models are used in data analysis. We will explicitly expand upon two points. Firstly, it is suboptimal to use Pearson correlations for rating scales which are of an ordinal nature. Pearson correlations do not represent the true relationships between ordinal variables and can lead to false factorial structures which have no reasonable substantive meaning (see the findings on "difficulty factors", e.g., Moosbrugger & Hartig, 2002). Secondly, if the state-trait distinction in the models used in data analysis is ignored, response styles can less easily be controlled for, because response styles are trait components which should be disentangled from situation-specific effects.

In the present paper we will show in a longitudinal study with ordinal mood state data that mood states are in fact bipolar. More specifically, we will show that the *deviation of a mood state* from the corresponding *mood trait* is a bipolar dimension that can be measured both by negatively and/or by positively formulated items. Whether items are positively or negatively formulated only makes a difference in the measurement of mood *trait*. As will be shown, traits assessed by negatively formulated items and the corresponding traits assessed by positively formulated items correlate to some degree, but not perfectly. However, the *deviations* of mood state from the corresponding mood trait do have a perfect negative correlation (–1) within each occasion of measurement.

11.2 Method

First of all, it should be noted that this study was not primarily designed for the purpose described above. However, the study contains information that can be used for testing our hypotheses. We concede that a new study with additional items and data would be more conclusive than the present one. Nevertheless, it seems worthwhile analyzing the data set that is available.

11.2.1 Description of the data

11.2.1.1 Sample

A sample of 291 females and 212 males between 17 and 77 years of age (mean age: 31.2 years) responded to a number of questionnaires on four occasions of measurement, each of which was three weeks apart. Among others, a mood state questionnaire, a mood trait questionnaire, a personality questionnaire, and a scale of daily hassles and uplifts were administered.[1] The subjects were paid DM 50 for completing the tests on all four occasions of measurement. About half of the subjects were assessed in group sessions in a lecture room at the University of Trier (Germany). The other half of the subjects were recruited via a snowball system and filled in their questionnaires at home (Steyer, Schwenkmezger, Eid & Notz, 1991).

The sample analyzed here consists of those among the 548 original subjects who delivered their questionnaires on all four occasions and who had no missing values on the items analyzed. Hence, depending on the item set (see next paragraph), the sample sizes varied between 470 and 501.

11.2.1.2 Items

The analyses to be presented refer to the items and scales of the German version of the Multidimensional Mood Questionnaire (Steyer, Schwenkmezger, Notz & Eid, 1997). This questionnaire has been designed to assess three bipolar dimensions of mood: feeling well vs. feeling bad (GS scale),

[1] The complete data set is available in the internet at http://www.uni-jena.de/svw/metheval/daten/start.html.

being awake vs. being tired (WM scale), feeling calm vs. feeling tense (RU scale). Table 1 contains a list of the German items for each of the three scales and their English translations. The subjects rated their mood state on a 5-point Likert scale ranging from 1, labeled “überhaupt nicht” (“not at all”), to 5, labeled “sehr” (“very much so”). The response categories between 1 and 5 were only labeled 2, 3, and 4 and had no verbal label.

Table 1. MDBF scales and their items

Scale	Short form A	Short form B
	zufrieden (content)	wohl (well)
	gut (good)	glücklich (happy)
GS	schlecht (bad)	unglücklich (unhappy)
	unwohl (unwell)	unzufrieden (discontent)
	ausgeruht (rested)	wach (awake)
	munter (lively)	frisch (fresh)
WM	schlapp (floppy)	schläfrig (sleepy)
	müde (tired)	ermattet (exhausted)
	gelassen (composed)	ruhig (calm)
	entspannt (relaxed)	ausgeglichen (well-balanced)
RU	ruhelos (restless)	angespannt (tense)
	unruhig (uneasy)	nervös (nervous)

11.2.2 Data Analysis

11.2.2.1 Methodological Background: Latent State-Trait Models

As mentioned in the introduction, our hypothesis is that the deviation of a mood state from its mood trait is a bipolar dimension that can be measured by negatively and/or by positively formulated items. How do we measure these deviations of a mood state from its mood trait? Within the framework of latent state-trait theory (LST theory) (see, e.g., Steyer, Ferring & Schmitt, 1992; Steyer, Schmitt & Eid, 1999) the answer is simple. A typical model of LST theory is the multistate-singletrait model (MSST model) with a method factor (Steyer et al., 1992) depicted in Figure 1. According to this model, a manifest variable Y_{it} observed on occasion t of measurement can be decomposed into a (linear function of a) *latent state variable* h_t that is common to all variables observed at time t and a *measurement error variable* e_{it}. Each latent state variable h_t can itself be decomposed into a (linear function of a) *latent trait variable* x that is assumed to be constant for all occasions of measurement considered, and a *latent state residual* z_t. Hence, this latent state residual z_t is the deviation of the mood state from its associated mood trait.

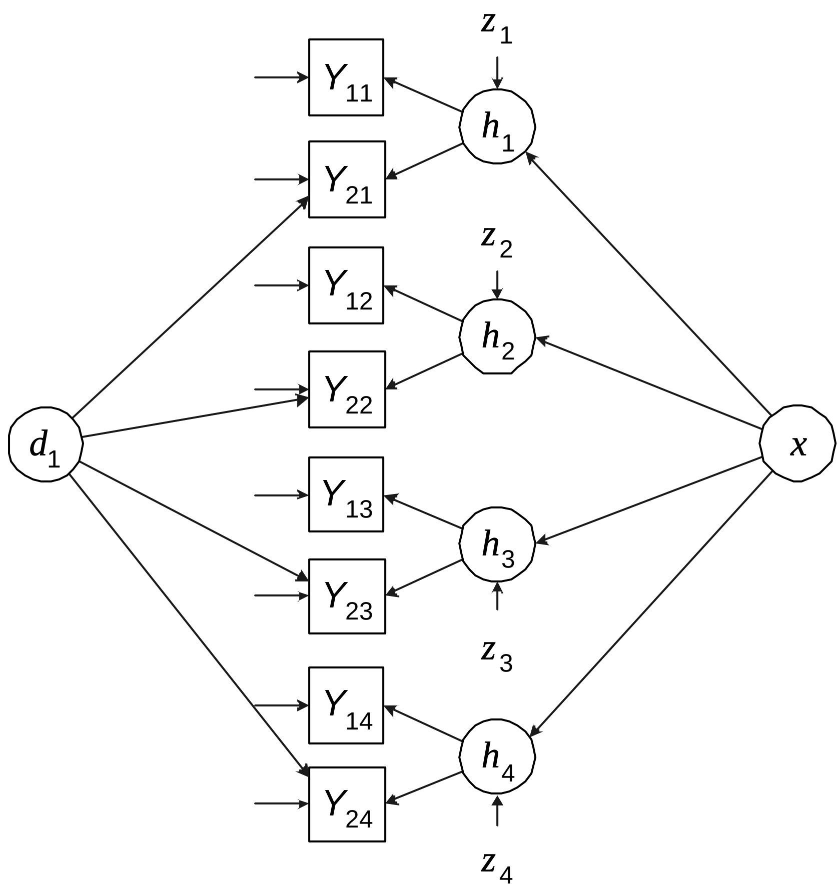

Figure 1. Conceptual path diagram of a multistate-singletrait model (MSST model) for two measures (tests or items) on each of four occasions of measurement with one method factor.

In many applications, the manifest variables Y_{it} are not perfectly parallel (or homogeneous) measures of the same latent state variable. In these cases a more realistic model also includes a "method factor" representing those method effects which vary between subjects (see the latent variable on the left-hand side of Figure 1). These methods factors are ordinary latent variables which usually have different scores. The scores of such a method factor can be interpreted as the effects of the interaction between subject and method, or, in other words, they represent the specific effects of the second measurement instrument for the specific person as compared to the reference method (i.e., the first instrument). The variances of these variables will reflect the degree of heterogeneity of the methods used to measure the latent state variable h_t. In these models, we need just one method factor less than there are different methods: one method factor for two methods, two (correlating) method factors for three methods, etc. Note that “method” in the present context usually means “parallel form” or “item”. Hence we will treat the self-ratings with respect to two items such as feeling “good” and feeling “well” as two different methods of assessing the mood state of well-being. Details and more about the rationale of models with method factors can be found in Eid (2000) and Eid et al. (2003).

Other LST models, involving several constructs and several traits can be found in Steyer et al. (1989) and Eid et al. (1994). Note that traits, in principle, can also change across time (see, e.g., Eid & Hoffmann, 1998) – although they are less variable than states which also fluctuate due to situation effects – and that there are also models with correlated test-specific (or item-specific) traits avoiding methods factors (Steyer et al., 1999). Furthermore, these models have also been developed for ordinal variables (Eid, 1996; 1997), an approach which will also be used in the present paper.

To summarize: The statistical modeling techniques used in this paper are based on (a) latent state-trait theory, (b) structural equation modeling with ordinal variables, and (c) the approach of Eid et al. (2003) of dealing with method factors.

11.2.2.2 Item Sets

Within the GS scale (good vs. bad), there are several items, which, semantically, are antonymous (i.e., they have opposite meanings): “gut” (good) and “schlecht” (bad), “zufrieden” (content) and “unzufrieden” (discontent), “wohl” (well) and “unwohl” (unwell), “glücklich” (happy) and “unglücklich” (unhappy). Within the WM scale (awake vs. tired) it is more difficult to find exact antonyms. However, the item pairs “wach” (awake) and “müde” (tired) as well as “munter” (lively) and “ermattet” (exhausted) may be rather close to being antonyms. Finally, in the RU scale we may choose “entspannt” (relaxed) and “angespannt” (tense) as well as “ruhig” (calm) and “unruhig” (restless) as antonymous adjectives.

The next strategy is to choose two positive items such as "gut", "zufrieden" (good, content) and their antonyms such as "schlecht", "unzufrieden" (bad, discontent). Four such items will be referred to as an *item set* in this paper. We will consider the six item sets displayed in Table 2. The question may be raised why we only select *two* positive and two negative items and not more. The reason for this is that the sample size is not large enough to allow more items to be modeled with programs for structural equation modeling of ordinal data (see, e.g., Eid, Mayer, Steyer, Notz & Schwenkmezger, 1993). Hence, we choose to work with the smallest possible model allowing us address our hypothesis.

Table 2. Item sets

Item set 1: "gut-zufrieden" vs. „schlecht-unzufrieden" ; *N* = 470
Item set 2: "wohl-glücklich" vs. „unwohl-unglücklich"; *N* = 486
Item set 3: "ruhig-entspannt" vs. „unruhig-angespannt"; *N* = 501
Item set 4: "wach-munter" vs. „müde-ermattet"; *N* = 488
Item set 5: "gut-wohl" vs. „schlecht-unwohl"; *N* = 490
Item set 6: "gut-wohl" vs. „angespannt-unruhig"; *N* = 499

Note: see Table 1 for English translations of the adjectives

From a substantive point of view, our hypothesis (that the deviations of mood states from their corresponding mood traits correlate −1) should hold perfectly for item sets 1, 2, 3, and 5, whereas it clearly should not hold for item set 6 which contains items from different scales: "gut" and "wohl" belong to the GS scale (good vs. bad), whereas "angespannt" and "unruhig" belong to the RU scale (calm vs. nervous). Whilst these scales are correlated, we do not expect a perfect negative correlation between the deviations of the mood states from their corresponding mood traits within set 6. This item set is only included in order to demonstrate that the high negative correlation between the deviations of the mood states from the mood traits is not an artefact but rather an important substantive finding. Finally, for item set 4 we expect slight deviations from our hypothesized −1 correlation, because the items are not perfect antonyms, as is the case for the item sets 1, 2, 3 and 5. Note that these hypotheses are unusually precise in the context of observational studies. Even if they should not hold perfectly, they may be useful in guiding our data analysis as well as future research.

11.2.2.3 Models

For each of these six item sets we consider four occasions of measurement and test the following models, the input files of which are given in the Appendix. *Model A* is the least restrictive model allowing, within each occasion of measurement, *any correlation* between the deviations of mood state from the corresponding mood trait. *Model B* is the *most restrictive model postulating a perfect negative correlation (i.e., equal to -1) between these deviations* within each occasion of measurement. In all models considered, the deviations of mood state from mood trait between occasions are assumed to be uncorrelated. Finally, in *Model C* we allow for a nonperfect negative correlation between these deviations within the first occasion of measurement, while postulating perfect negative correlations for times two to four. This exception is substantively meaningful, because the first occasion may be considered to be a "warming up" occasion of measurement in which subjects learn using the questionnaire (cf. Jagodzinski, Kühnel & Schmidt, 1987).

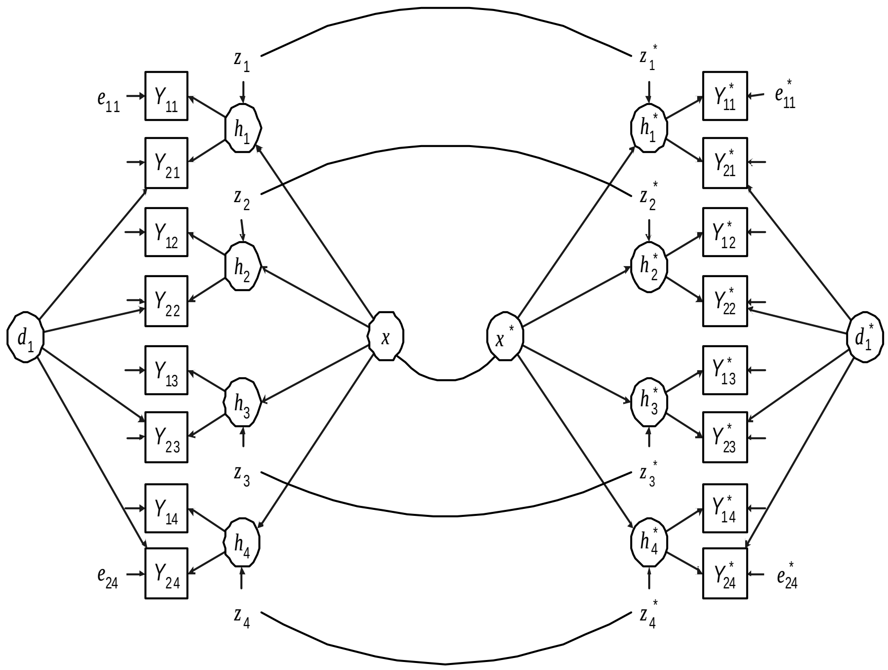

Figure 2. Conceptual path diagram of Model A: a two-construct model with one method factor and correlated latent state residuals

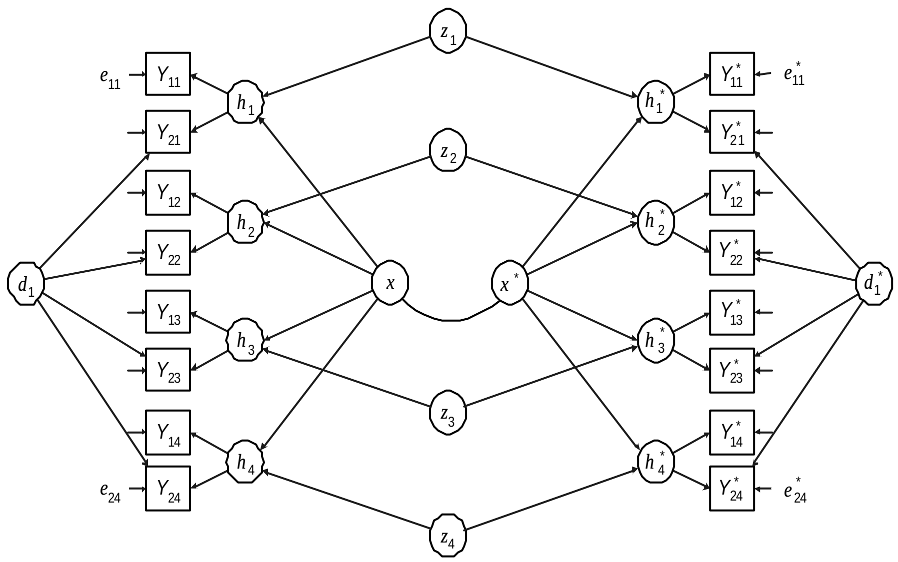

Figure 3. Conceptual path diagram of Model B: a two-construct model with one method factor and perfectly correlated latent state residuals

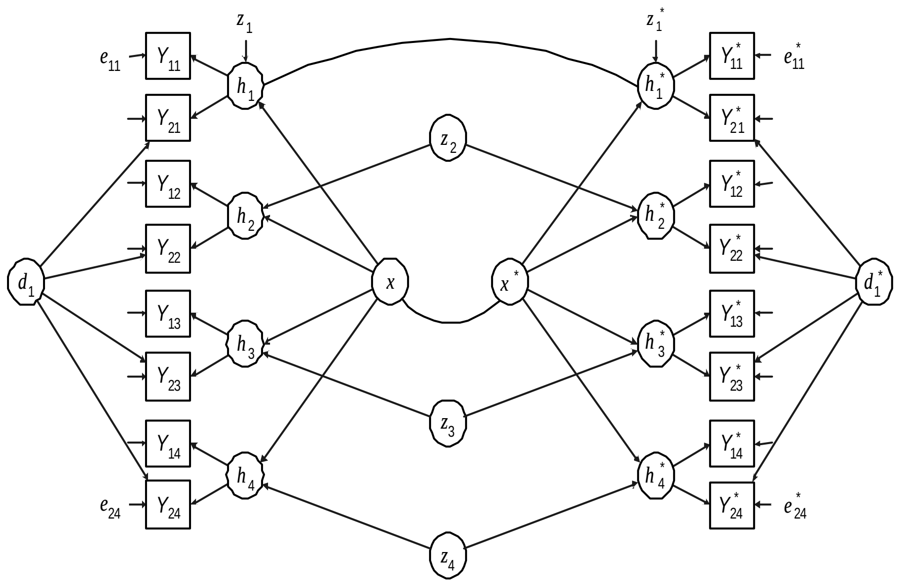

Figure 4. Conceptual path diagram of Model C: a two-construct model with one method factor and perfectly correlated latent state residuals for occasions two to four. At occasion one, latent state residuals correlate less than perfectly

Figures 2 to 4 present the models more explicitly. In all three models we assume that there is one trait for the positive items and a separate trait for the negative items. These two trait variables represent the *self-reported* mood traits. They have a high negative correlation which, however, is less than perfect. Our interpretation of this less than perfect correlation is that the subjects tend to react differently to positive and negative items and that these differences are subject-specific. That is, there are inter-individual differences (response styles) in responding to positive items and negative items, but these inter-individual differences are stable over time. Hence, the less than perfect correlation between the two latent trait variables is due to stable response styles biasing the response to the items.

The deviation of the mood state from this mood trait, however, is no longer biased. It veridically reflects the true deviation of the mood state from the mood trait. Therefore, it should no longer matter if this deviation is assessed via a positive or via a negative item.

The models in Figures 2 to 4 also contain two “method factors” or, more specifically, two “item-specific factors”. They are necessary to account for the semantic differences between the items such as “gut” (good) and “zufrieden” (content) or “schlecht” (bad) and “unzufrieden” (discontent). The smaller the proportion of variances determined by these item-specific factors, the more homogeneous these item pairs are. The details of the model specifications are given in the three input files in the Appendix.

11.2.2.4 Estimation Method

For each of the six item sets mentioned in the previous section, each of which consists of four items repeated at four time points, we computed a polychoric correlation matrix and the matrix of their asymptotic covariances using PRELIS 2 (Jöreskog & Sörbom, 1996). The polychoric correlation matrix was then analyzed with LISREL 8.52 (Jöreskog, Sörbom, du Toit & du Toit, 2001) using the matrix of asymptotic covariances with WLS-estimation. This way we take into account that the items have ordered response categories and we allow for different thresholds and difficulties of the items and also different thresholds for the response categories. By employing this method we can circumvent methodological artifacts such as difficulty factors (see, e.g., Moosbrugger & Hartig, 2002), which would occur if we treated the items as continuous (or metric) variables and then used the Pearson correlation. Furthermore, this method gives us meaningful information about the items and their response categories.

11.3 Results

We begin by looking at Table 3 containing the thresholds for each item of item set 2 at each of the four occasions of measurement. These thresholds characterize the items and their response categories. In order to understand their meaning we have to remember that for each item it is assumed that there is an underlying standard normal latent variable. The first threshold of item "wohl" (well) at time 1 of measurement, -1.737, is the *z*-score cutting off those 4.1% of all persons within the normal distribution who answered 1 ("not at all"). (These percentages can also be found in Table 4 displaying the marginal distributions of all four items of item set 2 at time 1 of measurement.) The second threshold, -0.793, cuts off those 4.1% plus the additional 17.3% of all subjects who answered in response category 2 of this item at the first occasion of measurement etc.

Table 3. Thresholds for item set 2 (Sample Size = 486)

Time	Item	Thresholds				Average Threshold (Location
1	wohl (well)	-1.737	-0.793	-0.015	1.118	-0.357
1	glücklich (happy)	-1.492	-0.772	0.224	1.254	-0.197
2	wohl (well)	-1.737	-0.967	-0.026	1.081	-0.412
2	glücklich (happy)	-1.540	-0.807	0.114	1.221	-0.253
3	wohl (well)	-1.812	-0.828	0.036	1.138	-0.367
3	glücklich (happy)	-1.432	-0.658	0.240	1.313	-0.134
4	wohl (well)	-1.593	-0.935	-0.010	1.118	-0.355
4	glücklich (happy)	-1.524	-0.793	0.140	1.243	-0.234
1	unwohl (unwell)	0.000	0.658	1.221	2.042	0.980
1	unglücklich (unhappy)	0.103	0.658	1.277	1.931	0.992
2	unwohl (unwell)	-0.088	0.704	1.265	2.042	0.981
2	unglücklich (unhappy)	0.176	0.737	1.350	1.868	1.033
3	unwohl	-0.088	0.620	1.221	2.186	0.985

Time	Item	Thresholds				Average Threshold (Location
	(unwell)					
3	unglücklich (unhappy)	0.161	0.731	1.446	1.899	1.059
4	unwohl (unwell)	-0.005	0.717	1.337	2.246	1.074
4	unglücklich (unhappy)	0.315	0.904	1.507	2.042	1.192

Table 4. Marginal distributions of the items from item set 2 on occasion 1.

	Wohl (well)		Glücklich (happy)		unwohl (unwell)		Unglücklich (unhappy)	
Response Category	Fre-quency	%	Fre-quency	%	Fre-quency	%	Fre-quency	%
1	20	4.1	33	6.8	243	50.0	263	54.1
2	84	17.3	74	15.2	119	24.5	99	20.4
3	136	28.0	179	36.8	70	14.4	75	15.4
4	182	37.4	149	30.7	44	9.1	36	7.4
5	64	13.2	51	10.5	10	2.1	13	2.7

Looking at Table 3 we can say that “wohl” (well) is the easiest item. “Difficulty” or “easiness” of an item can be defined in different ways, for example as the average threshold of an item or as the size of the last threshold indicating the point in the standard normal distribution at which all subjects exceeding this point answer in the last response category, or as the size of the first threshold indicating the point in the standard normal distribution at which all subjects below this point answer in the first response category. The item “glücklich” is somewhat more difficult which fully corresponds with the meaning and the German usage of these words. Much more dramatic is the difference between the positively and negatively formulated items. The last threshold of “unwohl” (unwell) is almost one unit (standard deviation) higher than the last threshold of “wohl”. Almost 50% of all subjects answer in response category 1 (“not at all”) of the item “unwohl” and more than 50% answer in this response category of the item “unglücklich” (unhappy). In principle it would be possible to impose equality constraints on the threshold between items and/or across time. However, in this application we did not employ this technique, because with the present version of PRELIS, we are still not able to *test* such an equality constraint.

Next we turn to the estimated correlations between the deviations of the mood states from the mood traits. According to our theory, these correlations should be −1 for item sets 1, 2, 3 and 5, close to −1 for item set 4, and distinctly not −1 for item set 6. These correlations which are estimated (via weighted least squares) under Model A described above are shown in the first four columns and their average in column 5 of Table 5. Note that, although true correlations cannot be smaller than −1, their WLS estimates can. Considering the average correlations displayed in column 5 shows that, from a descriptive point of view, our hypothesis holds close to perfectly for item sets 1, 2, 5, and less perfectly in item sets 3 and 4, in which the average correlations are −.913 and −.947, respectively. For item set 6 the correlations between the deviations of the mood states from the mood trait are, on average -0.699, which meets our expectation that perfect negative correlations only occur for antonyms (i.e., for items with semantically opposite meanings). Also the correlations between the trait components pertaining to positive and negative items are as expected. They are negative and high, but not close to −1. Furthermore, as expected, the correlation between traits is only −.596 for item set 6 (consisting of items from different scales), whereas it is between −.734 and −.846 for the other item sets.

Table 5. Trait correlations and correlations between latent state residuals within each occasion of measurement estimated in Model A

	t_1	t_2	t_3	t_4	average correlation of state residuals	trait correlation
Item set1	-0.888	-0.999	-1.052	-1.086	-1.006	-0.839
Item set2	-0.924	-0.996	-1.004	-0.914	-0.960	-0.846
Item set3	-0.878	-0.883	-0.941	-0.950	-0.913	-0.734
Item set4	-0.954	-0.977	-0.963	-0.893	-0.947	-0.776
Item set5	-0.987	-1.009	-1.024	-1.017	-1.009	-0.821
Item set6	-0.682	-0.661	-0.791	-0.661	-0.699	-0.596

Note: Note that, although true correlations cannot be smaller than −1, their WLS estimates can be smaller than −1. LISREL does not restrict the range of these estimates.

Table 6 gives the model fit statistics for Models A, B and C for each of the six item sets. Looking at the χ^2-goodness of fit statistics reveals that the model fits are close to perfect for item set 1 and 5, whilst the fits are not so perfect for models 2, 3 and 4. The root mean square error of residuals (RMSEA) are all smaller than .04 indicating that all models are quite acceptable. However, more important for our hypothesis is a *comparison* of the fit statistics between the three models, specifically looking at the χ^2-differences. For a test of our hypothesis we have to compare the χ^2-values between models A and B and between models A and C. Remember, *Model A* is the least restrictive model allowing, within each occasion of measurement, *any correlation* between the deviations of mood states from their mood traits. *Model B* is the most restrictive model postulating a perfect negative correlation (i.e., equal to -1) between these deviations within each of the four occasions of measurement. In *Model C* we allow for a nonperfect negative correlation between these deviations within the first occasion of measurement, while postulating perfect negative correlations for occasions two to four.

Table 6. Comparing the three models via χ^2-difference tests

	Model A; $df = 94$			Model B; $df = 98$			Model C; $df = 97$			A vs. C
	χ^2	p	RMSEA	χ^2	p	RMSEA	χ^2	p	RMSEA	
Item set 1	104.71	.21	.016	116.15	.10	.020	110.35	.17	.017	
Item set 2	155.07	.00	.037	162.05	.00	.037	156.88	.00	.036	
Item set 3	145.15	.00	.033	158.99	.00	.035	152.22	.00	.034	
Item set 4	133.83	.00	.029	165.22	.00	.038	161.98	.00	.037	*
Item set 5	104.23	.22	.015	105.40	.29	.012	105.22	.27	.013	
Item set 6	119.06	.04	.023	233.26	.00	.053	182.65	.00	.042	**

Note: The column headed A vs. C contains an asterisk if the corresponding χ^2-difference test is significant at the .05-level. The critical χ^2 for 3 degrees of freedom at the .05-level is 7.81.

Comparing model A to B shows that only item set 5 yields a χ^2-difference (105.40 − 104.23 = 1.17; *df* = 4) that is not significant at the .05-level. However, comparing model A to C yields much smaller χ^2-differences. These results indicate that Model A is preferable to Model C only for item sets 4 and 6. For item set 6, the difference (182.65 − 119.06 = 63.59; *df* = 3) is large as was expected, because this item set consists of items from different scales. Item set 4 containing the items “wach-munter vs. müde-ermattet” (awake-lively vs. tired-exhausted) is the set consisting of item pairs which are opposite in meaning but not as perfectly antonymous as the item sets 1, 2, 3 and 5. For the four sets within occasions 2 to 4, we do not have to reject the hypothesis that the deviations of mood states from their mood traits correlate −1.

11.4 Discussion

The results presented in Table 6 indicate that indeed the deviations of mood states from their mood traits are *bipolar*. However, this only applies perfectly for those occasions of measurement in which the subjects are already acquainted with the use of such a questionnaire (in our case: occasions two to four). Furthermore, this only holds for item pairs which can be considered to be exact antonyms (i.e., exact semantic opposites of each other) such as “good” (gut) and “bad” (schlecht) or “well” (wohl) and “unwell” (unwohl). The more the meanings of the adjectives differ from one another, the lower the negative correlations between the deviations of the mood states from the mood traits within an occasion of measurement. This fact is most obvious when we look at the analysis of item set 6 which contains items pertaining to different dimensions and scales (GS scale and RU scale) of the mood state questionnaire.

What conclusions can be drawn? Firstly, the measurement of mood traits via repeated measurement of mood states is biased by response sets. These measurements are specific for the items used and depend on whether or not items are formulated positively or negatively. Even if exact semantically opposite items are used, such as “good” and “bad”, the measurements will differ. Whilst they correlate, they are not perfectly functionally related, even when measurement error is taken into account. Instead there is an interaction (in the ANOVA sense) between the person factor and the factor “positivity vs. negativity” of the items. Hence, the highest reliability of the measurements can be reached if the scales contain either only positive or only negative items. The question of their validity is however, still open, that is, we do not yet know, if positively formulated items yield more valid measurements of the mood state to be assessed than negatively formulated items.

Secondly, when it comes to measuring the *deviations of mood states from their mood traits*, positive and negative items do equally well. Our results indicate that these deviations *are functionally* related. This also implies that the *changes* in mood states as assessed by a positive item and its negative counterpart are functionally related (i.e., a change rated on a positive item goes perfectly along with a change rated on a negative item). This can be used in experiments designed to *manipulate* mood states (see, e.g., Vautier & Raufaste, 2002).

Thirdly, a general and more substantive conclusion is that unsystematic measurement errors and systematic answer styles mask the deterministic relationship between self-ratings of antonymous mood state. A methodological conclusion is that multi-construct latent state-trait models are useful in controlling for unsystematic measurement error and systematic errors due to response styles. Such models may also be helpful in revealing the underlying dimensionality in related psychological areas such as the measurement of affect (Diener & Emmons, 1985; Schmukle, Egloff & Burns, 2002; Tellegen et al., 1999), or self-esteem (Marsh, 1996).

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Appendix 11.1 : LISREL input files

```
TI Model A described in the paper

DA  NI = 16  NO = 470  MA=PM

LA
Good1 Cont1 Good2 cont2 Good3 Cont3 Good4 Cont4
Bad1 Discon1 Bad2 Discon2 Bad3 Discon3 Bad4 Discon4

PM  FI = set1.pm
AC  FI = set1.acm

MO  NY=16    NE=12    LY=FU,FI    PS=SY,FI    TE=DI,FR
BE=FU,FI

LE
ETA1  ETA2  ETA3  ETA4
ETA*1 ETA*2 ETA*3 ETA*4
KSI   KSI*
```

```
MetF1  MetF*1

! Fixing the scales of the latent state variables
VALUE  1.0  LY(1,1)  LY(3,2)   LY(5,3)  LY(7,4)
VALUE  1.0  LY(9,5)  LY(11,6)  LY(13,7) LY(15,8)

! Set free other loadings on the latent state
! variables
FREE LY(2,1)   LY(4,2)   LY(6,3)  LY(8,4)
FREE LY(10,5)  LY(12,6)  LY(14,7) LY(16,8)

! Set free the variances of the method factors
FREE PS(11,11) PS(12,12)

! Fixing the scales of the method factors
VALUE  1.0  LY(2,11)  LY(10,12)

! Set free the loadings of the method factors
FREE LY(4,11) LY(6,11) LY(8,11)
FREE LY(12,12) LY(14,12) LY(16,12)
START 1.0 LY(4,11) LY(6,11) LY(8,11)
START 1.0 LY(12,12) LY(14,12) LY(16,12)

! Set free the variances of the latent trait variables
FREE PS(9,9) PS(10,10)

!Fixing the scales of the Traits
VALUE 1.0 BE(1,9) BE(5,10)

! Set free the effects of the Traits
FREE  BE(2,9) BE(3,9) BE(4,9)
FREE  BE(6,10) BE(7,10) BE(8,10)

ST 1.0 BE(2,9) BE(3,9) BE(4,9)
ST 1.0 BE(6,10) BE(7,10) BE(8,10)
ST 0.7 PS(9,10)

! Set free the covariances between the latent traits
FREE  PS(9,10)

! Set free the covariances between the method factors
```

```
FREE  PS(11,12)

! Set free the variances of the latent state residuals
FREE PS(1,1)  PS(2,2)  PS(3,3)  PS(4,4)
FREE PS(5,5)  PS(6,6)  PS(7,7)  PS(8,8)

! Set free the covariances between the latent state
residuals
FREE PS(1,5)  PS(2,6)  PS(3,7)  PS(4,8)

EQUAL   TE(1,1)   TE(3,3)    TE(5,5)    TE(7,7)
EQUAL   TE(2,2)   TE(4,4)    TE(6,6)    TE(8,8)
EQUAL   TE(9,9)   TE(11,11)  TE(13,13)  TE(15,15)
EQUAL   TE(10,10) TE(12,12)  TE(14,14)  TE(16,16)

PD
OU ND=3 WP SI=LISOUT.MAT AD=OFF MI SE SC
```

TI Model B described in the paper

```
DA  NI = 16  NO = 470  MA=PM

LA
Good1 Cont1 Good2 cont2 Good3 Cont3 Good4 Cont4
Bad1 Discon1 Bad2 Discon2 Bad3 Discon3 Bad4 Discon4

PM  FI = set1.pm
AC  FI = set1.acm

MO  NY=16    NE=16    LY=FU,FI    PS=SY,FI    TE=DI,FR
BE=FU,FI

LE
ETA1  ETA2  ETA3  ETA4
ETA*1 ETA*2 ETA*3 ETA*4
KSI   KSI*
MetF1  MetF*1
Zeta1 Zeta2 Zeta3 Zeta4

!Fixing the scales of the latent state variables
VALUE  1.0  LY(1,1)  LY(3,2)  LY(5,3)  LY(7,4)
```

```
VALUE  1.0  LY(9,5)  LY(11,6)  LY(13,7) LY(15,8)

! Set free the other loadings on the latent state
! variables
FREE LY(2,1)  LY(4,2)  LY(6,3)  LY(8,4)
FREE LY(10,5)  LY(12,6)  LY(14,7) LY(16,8)

! Set free the variances of the method factors
FREE PS(11,11) PS(12,12)

! Fixing the scales of the method factors
VALUE  1.0  LY(2,11)  LY(10,12)

! Set free the loadings of the method factors
FREE LY(4,11) LY(6,11) LY(8,11)
FREE LY(12,12) LY(14,12) LY(16,12)
START 1.0 LY(4,11) LY(6,11) LY(8,11)
START 1.0 LY(12,12) LY(14,12) LY(16,12)

! Set free the variances of the latent trait variables
FREE PS(9,9) PS(10,10)

! Fixing the scales of the Traits
VALUE 1.0 BE(1,9) BE(5,10)

! Set free the effects of the Traits
FREE  BE(2,9) BE(3,9) BE(4,9)
FREE  BE(6,10) BE(7,10) BE(8,10)

ST 1.0 BE(2,9) BE(3,9) BE(4,9)
ST 1.0 BE(6,10) BE(7,10) BE(8,10)
ST 0.7 PS(9,10)

! Set free the covariances between the latent traits
FREE  PS(9,10)

! Set free the covariances between the method factors
FREE  PS(11,12)

! Set free the variances of the common latent state
! residuals
```

```
FREE PS(13,13) PS(14,14) PS(15,15) PS(16,16)
ST 0.5 PS(13,13) PS(14,14) PS(15,15) PS(16,16)

! Fix the loadings of the common latent state
! residuals
VALUE  1.0 BE(1,13) BE(2,14) BE(3,15) BE(4,16)
FREE       BE(5,13) BE(6,14) BE(7,15) BE(8,16)
START -1.0 BE(5,13) BE(6,14) BE(7,15) BE(8,16)

EQUAL   TE(1,1)   TE(3,3)    TE(5,5)    TE(7,7)
EQUAL   TE(2,2)   TE(4,4)    TE(6,6)    TE(8,8)
EQUAL   TE(9,9)   TE(11,11)  TE(13,13)  TE(15,15)
EQUAL   TE(10,10) TE(12,12)  TE(14,14)  TE(16,16)

PD
OU WP SI=LISOUT.MAT AD=OFF MI SE SC
```

TI Model C described in the paper

```
DA  NI = 16  NO = 470  MA=PM

LA
Good1 Cont1 Good2 cont2 Good3 Cont3 Good4 Cont4
Bad1 Discon1 Bad2 Discon2 Bad3 Discon3 Bad4 Discon4

PM  FI = set1.pm
AC  FI = set1.acm

MO NY=16 NE=16 LY=FU,FI PS=SY,FI TE=DI,FR BE=FU,FI

LE
ETA1  ETA2  ETA3  ETA4
ETA*1 ETA*2 ETA*3 ETA*4
KSI   KSI*
MetF1  MetF*1
Zeta1 Zeta2 Zeta3 Zeta4

! Fixing the scales of the latent state variables
VALUE  1.0  LY(1,1)  LY(3,2)  LY(5,3)  LY(7,4)
VALUE  1.0  LY(9,5)  LY(11,6)  LY(13,7) LY(15,8)
```

```
! Set free the other loadings on the latent state
! variables
FREE LY(2,1)  LY(4,2)  LY(6,3)  LY(8,4)
FREE LY(10,5)  LY(12,6)  LY(14,7) LY(16,8)

! Set free the variances of the method factors
FREE PS(11,11) PS(12,12)

! Fixing the scales of the method factors
VALUE  1.0  LY(2,11)  LY(10,12)

! Set free the loadings of the method factors
FREE LY(4,11) LY(6,11) LY(8,11)
FREE LY(12,12) LY(14,12) LY(16,12)
START 1.0 LY(4,11) LY(6,11) LY(8,11)
START 1.0 LY(12,12) LY(14,12) LY(16,12)

! Set free the variances of the latent trait variables
FREE PS(9,9) PS(10,10)

! Fixing the scales of the Traits
VALUE 1.0 BE(1,9) BE(5,10)

! Set free the effects of the Traits
FREE  BE(2,9) BE(3,9) BE(4,9)
FREE  BE(6,10) BE(7,10) BE(8,10)

ST 1.0 BE(2,9) BE(3,9) BE(4,9)
ST 1.0 BE(6,10) BE(7,10) BE(8,10)
ST 0.7 PS(9,10)

! Set free the covariances between the latent traits
FREE  PS(9,10)

! Set free  the covariances between the method factors
FREE  PS(11,12)

! Set free the variances of the common latent state
! residuals
FREE PS(13,13) PS(14,14) PS(15,15) PS(16,16)
ST 0.5 PS(13,13) PS(14,14) PS(15,15) PS(16,16)
```

```
! Fix loadings of the common latent state residuals
VALUE  1.0 BE(1,13) BE(2,14) BE(3,15) BE(4,16)
VALUE -1.0 BE(5,13)
FREE                BE(6,14) BE(7,15) BE(8,16)
START -1.0          BE(6,14) BE(7,15) BE(8,16)

! Set free the variances of the latent state residuals
! for the first occasion of measurement
FREE PS(1,1) PS(5,5)

EQUAL   TE(1,1)   TE(3,3)    TE(5,5)    TE(7,7)
EQUAL   TE(2,2)   TE(4,4)    TE(6,6)    TE(8,8)
EQUAL   TE(9,9)   TE(11,11)  TE(13,13)  TE(15,15)
EQUAL   TE(10,10) TE(12,12)  TE(14,14)  TE(16,16)

PD
OU WP SI=LISOUT.MAT AD=OFF MI SE SC
```